Smart Monitoring System for Employee Performance Evaluation: Deep Learning-Based Predictive Analysis

Abstract

Employee performance evaluation is a critical process within organizations; however, the traditional methods still in use tend to be subjective and fail to make optimal use of historical data. This study aims to design and develop a Deep Learning-based intelligent monitoring system capable of supporting employee performance evaluations in a more objective, adaptive, and data-driven manner. The research method used is Design Science Research (DSR), which includes the stages of problem identification, goal setting, design and development, demonstration, and system evaluation. The system was developed by integrating Angular frontend technology, .NET Core Web API backend, SQL Server database, and a Deep Learning model based on Long Short-Term Memory (LSTM). The system is capable of generating several key outputs, namely efficiency scores, employee performance categories, and predictions of future workloads based on historical data patterns. System evaluation using the System Usability Scale (SUS) method yielded a score of 74, indicating that the system has a good level of usability and is acceptable to users. Thus, the developed system is capable of serving as a more objective performance evaluation solution and supporting data-driven decision-making.

Keywords:

Smart Monitoring, Employee Performance Evaluation, Deep Learning, LSTM, System Usability Scale

1. Introduction

Employee performance evaluation plays an important role in improving organizational productivity and operational effectiveness. However, traditional evaluation methods are often subjective, inconsistent, and limited in utilizing historical performance data effectively. In many organizations, manual and semi-digital evaluation systems are still widely used, creating challenges in developing objective and data-driven evaluation processes.

In the era of Industry 4.0, Smart Manufacturing Systems (SMS) enable real-time monitoring and intelligent decision-making through continuous data processing. Employee performance has become a critical factor that directly affects organizational efficiency and productivity. Therefore, modern organizations require adaptive and predictive systems capable of evaluating employee performance more objectively.

Deep Learning approaches, especially Long Short-Term Memory (LSTM), have shown strong capabilities in handling temporal and sequential data. Several previous studies have applied Machine Learning and Deep Learning techniques for predictive analysis; however, most studies mainly focus on theoretical model development without providing integrated and practical system implementations.

Therefore, this study proposes a Smart Monitoring system for employee performance evaluation using Deep Learning-based predictive analysis. The proposed system integrates Angular, .NET Core Web API, SQL Server, and LSTM-based models within a full-stack architecture. This research adopts the Design Science Research (DSR) methodology to develop and evaluate an adaptive, objective, and data-driven employee performance evaluation system.

2. Related Work

Several studies have explored the use of Machine Learning and Deep Learning for employee performance evaluation and predictive analysis (Nayem & Uddin, 2024). Applied Machine Learning algorithms such as Logistic Regression, Random Forest, and Support Vector Machine (SVM) to reduce subjectivity in employee evaluation (Chen et al., 2025). Meanwhile, demonstrated that Long Short-Term Memory (LSTM) models perform effectively in handling temporal and sequential prediction problems (da Silva & Meneses, 2023).

In addition, showed that Deep Learning techniques significantly improve prediction accuracy in complex datasets (Yewle et al., 2025). However, most previous studies mainly focus on predictive model performance and theoretical analysis without implementing integrated Smart Monitoring systems or practical application artifacts. Therefore, this study addresses the existing research gap by developing an integrated Smart Monitoring system that combines LSTM-based predictive models with Angular frontend, .NET Core Web API backend, SQL Server database, and real-time monitoring features to support objective employee performance evaluation

3. Methodology

3.1 Research Method

This study uses the Design Science Research (DSR) methodology, which focuses on developing and evaluating artifacts to solve real-world problems (Perossa et al., 2026).

The Design Science Research (DSR) methodology applied in this study is illustrated in Figure 8. The process consists of several main stages, including problem identification, objective definition, design and development, demonstration, and evaluation. This structured approach ensures that the developed Smart Monitoring system is not only designed based on identified problems but also validated through systematic testing and user evaluation.

Figure 1 Design Science Research

3.2 System Architecture

The system is designed using a modular architecture consisting of Angular (frontend), .NET Core Web API (backend), SQL Server (database), and a Deep Learning module using Python (Flask API). This approach follows the separation of concerns principle, enabling scalability and maintainability (Frąszczak, 2022).

3.3 Dataset and Features

The dataset used in this study was obtained from a public Kaggle dataset containing employee work performance records. The dataset was utilized as secondary data for training, testing, and evaluating the Deep Learning models. Before model training, the dataset underwent several preprocessing stages, including data cleaning, normalization, feature transformation, and time-series formatting to ensure compatibility with the LSTM architecture.

Several main features were used in the predictive analysis process, including *WorkDate*, *FinishedToday*, *AvgWorkmanship*, *TotalWorkmanship*, *EfficiencyScore*, *PerformanceCategory*, and *UserId*. These features were used to support regression, classification, and workload prediction tasks within the Smart Monitoring system.

3.4 Deep Learning Models

Three LSTM-based models are implemented:

1. Regression model for efficiency score prediction
2. Time series model for workload prediction
3. Classification model for performance categorization

LSTM is selected due to its ability to capture temporal patterns and long-term dependencies (Chen et al., 2025).

4. Result and Discussion

4.1 System Implementation

The Smart Monitoring system was successfully implemented with full integration between frontend, backend, database, and Deep Learning models. The system provides dashboards that display performance data and predictions in real-time.

The Smart Monitoring system provides two main dashboards for different user roles, namely Operator and Engineer. As shown in Figure 1, the Operator Dashboard presents individual performance metrics such as efficiency score, daily workload, and historical task logs, enabling users to monitor their performance in real-time.

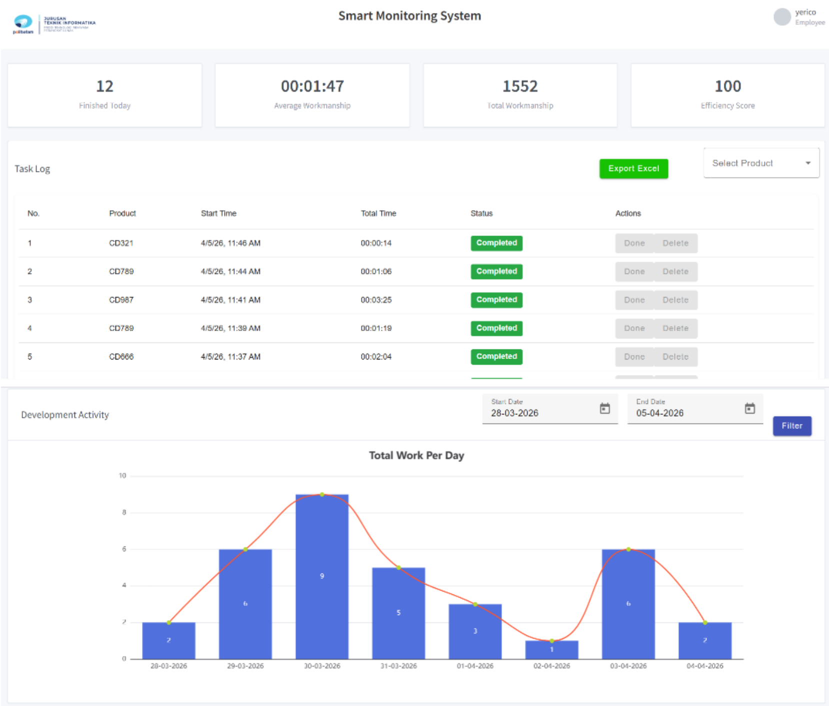

Figure 2 Dashboard Operator

Furthermore, the Engineer Dashboard, illustrated in Figure 2, provides a comprehensive overview of team performance, including workload distribution and predictive insights generated by Deep Learning models. This allows engineers to analyze team productivity and support decision-making processes.

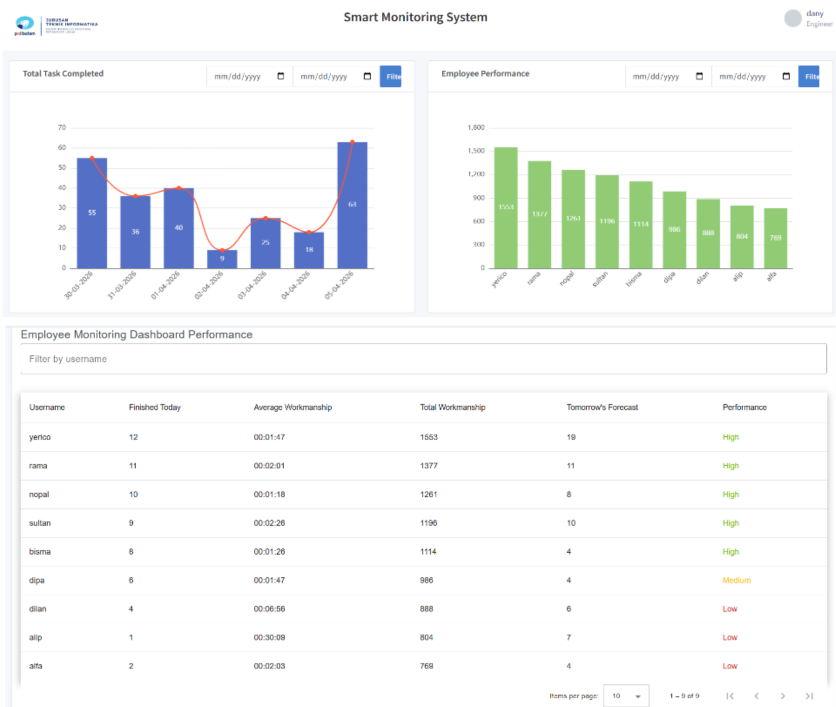

Figure 3 Dashboard Engineer

The database structure used in the system is illustrated in Figure 3. The ER diagram shows the relationship between entities such as users, work logs, and performance summaries, which serve as the main data source for the prediction models.

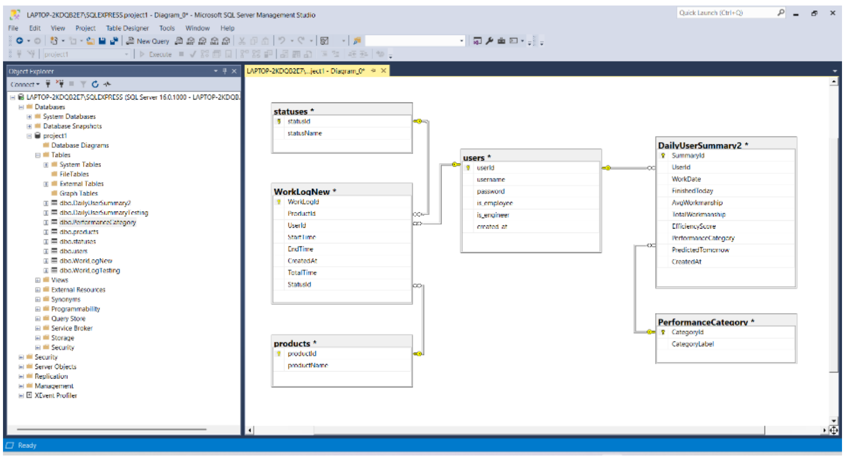

Figure 4 ER Diagram in SQL Server Management Studio 20

In addition, the backend API implementation is presented in Figure 4. The system uses RESTful API to enable communication between the frontend and Deep Learning modules, ensuring real-time data processing.

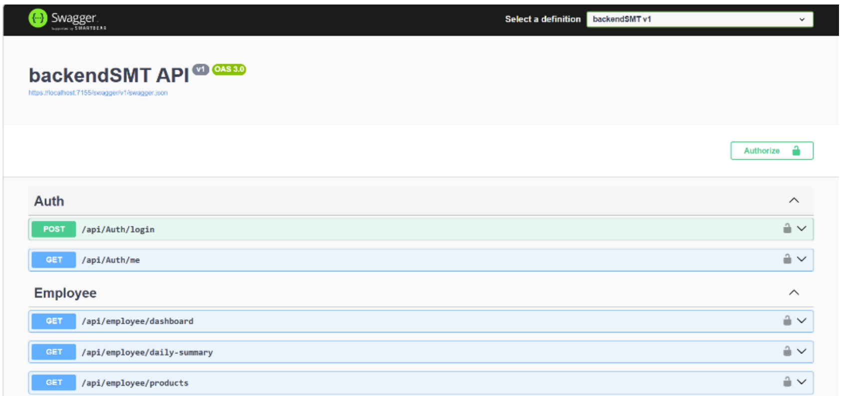

Figure 5 backendSMT API

4.2 Model Performance

The regression model produces efficiency scores within the defined range (0–100). The time series model predicts future workload based on historical data patterns, while the classification model categorizes performance into Low, Medium, and High. These results indicate that the models effectively capture data patterns and produce consistent outputs.

The testing results of the Deep Learning models are shown in Figure 5. The results demonstrate that the regression, time series, and classification models are able to generate consistent and meaningful outputs based on the given input data. This confirms that the models are functioning as expected and suitable for integration into the system.

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SMART MONITORING SYSTEM - MODEL TESTING
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[1] Memprediksi Skor Efisiensi Menggunakan Regression Model Berbasis Deep Learning (LSTM)

Input: 7 Hari Sebelumnya Dari Hari Ini
[[  32 1080 1800]
 [  22  565 1845]
 [  69 2880 1797]
 [  50 2010 1909]
 [  30 1035 2030]
 [  70 3131  890]
 [  48 1951  789]]

Output : Efficiency Score = 14

Metrics:
MAE  : 0.0232
RMSE : 0.0312

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[2] Memprediksi Pekerjaan Yang di Selesaikan Di Hari Berikutnya Menggunakan Time Series Model Berbasis Deep Learning (LSTM)

Input: 7 Hari Sebelumnya Dari Hari Ini
[[ 12 600 291   1]
 [ 17 520 291   1]
 [  8 420 291   0]
 [  3 610 291   0]
 [  5 408 291   1]
 [ 20 540 291   2]
 [  8 480 291   1]]

Output : Predicted FinishedTomorrow = 44

Metrics:
MAE  : 16.0293
RMSE : 25.6934

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 [3] Memprediksi Performa Karyawan Menggunakan Classification Model Berbasis Deep Learning (LSTM)

 Input: 7 Hari Sebelumnya Dari Hari Ini
 [[  32 1080 1800    1]
  [  22  565 1845    0]
  [  69 2880 1797    2]
  [  50 2010 1909    1]
  [  30 1035 2030    0]
  [  70 3131  890    2]
  [  48 1951  789    1]]

 Output:
 Class      : 0
 Label      : Low

 Metrics:
 Accuracy : 0.9320

 Classification Report:
               precision    recall  f1-score   support

            0       0.96      0.97      0.96      9007
            1       0.92      0.90      0.91      6087
            2       0.85      0.88      0.86      1588

     accuracy                           0.93     16682
    macro avg       0.91      0.91      0.91     16682
 weighted avg       0.93      0.93      0.93     16682


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 SEMUA MODEL BERHASIL DIUJI
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Figure 6 Testing Model

4.3 System Evaluation

System evaluation was conducted using the System Usability Scale (SUS). The system achieved a score of 74, categorized as “Good” (Xavier et al., 2025). This indicates that the system is easy to use, well-integrated, and acceptable to users. The results also demonstrate that the system reduces subjectivity in performance evaluation and supports data-driven decision-making.

The overall usability evaluation results are presented in Figure 6. The system achieved an average System Usability Scale (SUS) score of 74, indicating that the system falls into the “Good” category. This result demonstrates that users perceive the system as easy to use, well-structured, and effective in supporting performance monitoring activities.

Skor Hasil Hitung										Jumlah	Nilai
Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10		(Jumlah x 2.5)
4	4	4	4	4	4	4	4	4	4	40	100
4	2	4	2	4	1	2	3	4	3	29	73
4	4	4	3	4	4	4	4	4	4	39	98
4	2	3	1	4	2	4	3	3	2	28	70
3	1	3	2	2	1	3	1	3	1	20	50
3	3	3	2	3	4	3	4	2	3	30	75
2	2	2	2	2	2	2	2	2	2	20	50
4	4	4	4	4	4	4	4	4	4	40	100
3	3	3	3	3	3	3	3	3	3	30	75
3	2	4	2	2	1	2	1	4	0	21	53
3	3	4	3	4	4	2	4	3	4	34	85
3	3	2	2	3	3	3	3	2	0	24	60
4	4	2	4	4	4	4	2	1	3	32	80
2	3	3	3	3	3	2	3	2	3	27	68
4	4	4	4	4	4	4	2	2	2	34	85
4	2	4	2	4	2	2	2	4	4	30	75
4	2	4	2	4	2	3	2	4	2	29	73
3	3	3	3	4	4	4	4	3	3	34	85
3	2	3	1	3	3	3	3	3	3	27	68
4	4	4	4	4	4	4	4	4	2	38	95
4	3	4	2	4	1	4	1	4	2	29	73
3	2	2	1	3	2	2	2	2	1	20	50
4	3	3	0	2	4	2	3	3	0	24	60
2	3	3	3	4	3	3	4	2	3	30	75
4	3	4	2	4	2	3	2	4	2	30	75
2	2	3	2	4	2	4	3	3	3	28	70
2	3	3	2	4	1	2	2	3	2	24	60
4	3	4	2	4	3	3	3	4	3	33	83
4	2	3	2	4	2	2	3	3	2	27	68
Skor Rata-Rata (Hasil Akhir)											74

Figure 7 Final SUS Score

Furthermore, the classification of the SUS score is illustrated in Figure 7. Based on standard SUS interpretation, a score of 74 is categorized as “Good,” which indicates a high level of user acceptance. This suggests that the system not only functions correctly from a technical perspective but also provides a positive user experience.

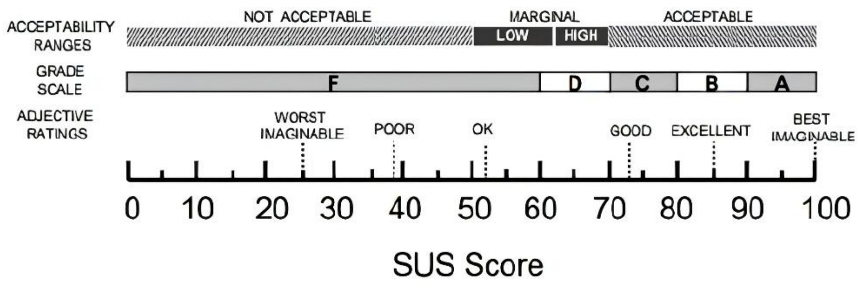

Figure 8 SUS Score Classification

5. Conclusion

This study successfully developed a Smart Monitoring system based on Deep Learning for employee performance evaluation. The system integrates multiple technologies and provides predictive insights, including efficiency scores, performance categories, and workload forecasts.

The results show that the system improves objectivity and usability, as indicated by the SUS score. Therefore, the proposed system can serve as an effective solution for modern performance evaluation.

6. Future Work

Future research should utilize real-world datasets to improve model validity. Further improvements can include enhancing model architectures, adding recommendation features, and deploying the system in real industrial environments.

7. References

Chen, Z., Zong, Y., Wang, S., & Li, D. (2025). Journal of Hydrology : Regional Studies Improving estuarine discharge forecasting with a KAN-augmented LSTM model : A case study of the Yangtze River Estuary. *Journal of Hydrology: Regional Studies*, *62*(November), 102961. https://doi.org/10.1016/j.ejrh.2025.102961

da Silva, D. G., & Meneses, A. A. de M. (2023). Comparing Long Short-Term Memory (LSTM) and bidirectional LSTM deep neural networks for power consumption prediction. *Energy Reports*, *10*(May), 3315–3334. https://doi.org/10.1016/j.egyr.2023.09.175

Frąszczak, D. (2022). NEFBDAA —.NET Environment for Building Dynamic Angular Applications. *SoftwareX*, *19*, 101163. https://doi.org/10.1016/j.softx.2022.101163

Nayem, Z., & Uddin, M. A. (2024). Unbiased employee performance evaluation using machine learning. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100243. https://doi.org/10.1016/j.joitmc.2024.100243

Perossa, D., Rosa, P., & Terzi, S. (2026). Corporate raw materials criticality assessment : A novel tool for car electronics value chains developed with design science research methodology. *Journal of Environmental Management*, *398*(December 2025), 128555. https://doi.org/10.1016/j.jenvman.2026.128555

Xavier, J., Lopes, R. P., & Pedro, R. (2025). *ScienceDirect Validation User Experience in Cognitive Rehabilitation Validation User Experience in Cognitive Rehabilitation Validation User Experience in Cognitive*. https://doi.org/10.1016/j.procs.2026.03.114

Yewle, A. D., Mirzayeva, L., & Karakuş, O. (2025). Remote Sensing Applications : Society and Environment Multi-modal data fusion and deep ensemble learning for accurate crop yield prediction. *Remote Sensing Applications: Society and Environment*, *38*, 101613. https://doi.org/10.1016/j.rsase.2025.101613